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AUTHOR Garson, G. David
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ABSTRACT

Most of what may be construed as political science has always proceeded through induction, which depends heavily on the insight, intuition, and personal brilliance of the particular author. Another approach that is closely associated with the early induction through examples is the expert system. The outcomes of this approach are not measures of the strength of association among variables, but are sets of rules which explain all or perhaps most of the given examples. Expert systems, however, are not a panacea. There is controversy about which algorithms are best and most efficient in automating the generation of expert rule sets. The computer software used in this essay to illustrate social science application of expert systems is based on classification and rule development procedures called "ID 3," developed by J. Ross Quinlan (1983) on the basis of work by Hunt and Stone (1966) on the "Concept of Learning System." It is 1st-Class, Version 3, from Programs in Motion, Inc., which runs on the IBM PC/XT/AT series. The example selected is a reanalysis of data presented by Wayne L. Francis on factors thought to determine the variance in the extent to which state legislators are satisfied with legislative outcomes. Expert systems suggest that it is appropriate to have a long time to consider bills and reject many of them. It is inappropriate to have a short time to consider bills and then accept most. If time is short, it is still inappropriate if one is being inundated with bills from the other chamber. (BZ)

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The Role of Inductive Expert Systems Generators in the Social Science Research Process

by G. David Garson
Department of Political Science & Public Administration
North Carolina State University
NCSU Box 8101
Raleigh, N.C. 27695

(919) 737-2468

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The Role of Inductive Expert Systems Generators in the Social Science Research Process

Most of what may be broadly construed as political science has always proceeded through induction. There are, of course, some aspects of both classical political theory and even modern work that are based on deductive logic, as in the use of economic marketplace principles to explain voting behavior (Downs, 1957), or in the application of game theory to explanation of the Watergate scandal of the Nixon era (Muzzio, 1982; see also Zagare, 1984). Nonetheless, induction, not deduction, has been the rule.

Early work on the "science" of politics was almost entirely non-quantitative, using inference from examples to construct rich theories of political reality, as in de Tocqueville's Democracy in America (1954). The merit of this form of induction depended heavily on the insight, intuition, and personal brilliance of the particular author. With the advent of better forms of data collection and the rise of the discipline of statistics, social scientists shifted from the earlier intuitive approach toward a quantitative form of induction based on empirical measurement and correlation.

With the rise of the statistical approach to social science data a premium was placed on probabilistic explanations. Even research on categorical data relied heavily on measures of association and the significance thereof. This line of research,

from simple chi-square tests through recent emphases on log linear analysis, has caused social scientists to forget that another approach to categorical data exists.

That other approach is more closely associated with earlier induction through example (see Hunt, Marin, and Stone, 1966). The outcomes of this other approach are not measures of strength of association among variables. Rather the outcomes are sets of rules which explain all or perhaps most of the given examples. Natural science gives numerous examples of this sort of categorical analysis, such as the rule sets associated with the chart of elements in chemistry or those associated with the definition of species in biology and botany.

I. What is an Expert System?

In fact, many of us have used just such rule sets. For example, we may have used a nature guide to birds, plants, or insects. In such guides, e.g., for trees, one first applies the rule of leaf type (needle or broad leaf), then the rule of leaf position (opposite or alternate), and so on until one has branched through the rules to arrive at a specific identification of species and subspecies.

Such rule sets are increasingly common in management (Harmon and King, 1983; Fersko-Weiss, 1985). A simple example would be the set of rules governing quality control: if certain defects are noted, then certain actions are taken. At the simplest level these rule sets are so intuitive that they seem mere common sense. In actual application, however, a rule set governing areas such as the recruitment of policemen, the

selection of an appropriate computer configuration, or responses in the play of chess, can become very complex.

The collected sets of rules which explain something (e.g., which individual to hire, which move to make in chess) are called expert systems. There are two major methods of creating an expert system: the rule-based approach and the example-based approach. The former is a top-down method which starts with rule sets, perhaps supplied by various experts in the field, and then determines which set or combination of sets best explains the given examples. The latter approach applies various algorithms to the given examples to induce the appropriate set of rules which can explain the result.

While both the rule-based and the example-based approach have value to social science, it is the latter which is most interesting and practical. The example-based approach is premised on the concept that rules can be induced to explain all the examples for any variable in any rectangular data matrix. It should be possible for any researcher - undergraduate students in research methods classes, for example - to induce such rule sets. These rule sets are not, of course, the "correct answers" but they may be highly useful as hypotheses in the exploratory phases of research.

Decision support programs must be distinguished from expert systems. Multi-critera decision-making programs (Radcliff, 1986) facilitate selection of one alternative among many through a system of paired comparison, weighting, and ranking. Although they may serve a valuable purpose by allowing decision-makers to articulate and weight evaluative criteria, this genre of software

is quite different from inductive expert systems which apply algorithms to generate rule sets capable of recommending or predicting outcomes of interest based on examples of past experience.

Expert systems are not a panacea (cf. Head, 1986). There is controversy about which algorithms are best and most efficient in automating the generation of expert rule sets. Moreover, the less relation that exists between the dependent variable and the others in the matrix, the more arbitrary and complex the rule set must become - often to the point of uselessness, where a complex and unique rule must exist to explain each case.

It is also true that expert systems approaches are not entirely "new and different" compared to standard statistical methods. A simple measure of the percentage of examples explained by the expert system's leading rules, for instance, is a form of measure of association for categorical variables. Algorithms for selecting cutting points on continuous variables for purposes of rule construction are analogous to principles often used in crosstabular research familiar to social scientists. And the function of expert systems in formulating recommendations or predictions based on case examples is one quite similar to that of multiple regression and related techniques.

In spite of the limitations of and statistical alternatives to analyses of social and political phenomena through expert systems, expert systems remain a methodology with great but unexploited potential for social science. First, just as expert systems may be applied to natural science, to management, or to

chess, so they may be applied to matters of interest to social scientists such as the explanation of voting, of discrimination, or of legislative decision-making. Second, social scientists generally will have less stringent demands on expert systems than, say, those in managerial environments. Where management applications may require rules which completely account for every possible case and where there is a question of legal liability for imperfect expert systems (Brown, 1986), social scientists will be apt to be interested in whether a relatively concise set of leading rules will account for a substantial number of examples. And where managers may wish to use expert systems in environments where there is little margin for error, social scientists will be likely to want to use expert systems for the exploratory phase of research, to generate hypotheses which later can be confirmed through more traditional analyses. (For further introduction see Van Horn, 1986; Williamson, 1986).

II. What is an Expert System Generator?

A. Automatic Generation of Expert Systems

The algorithms used to generate expert rule sets from data matrices are complex, reiterative, and too tedious for manual calculation. Computing, however, has made this approach feasible and microcomputing has made it inexpensive and convenient. In fact, microcomputer-based expert systems constitute one of the fastest growing genres of software (Grafton and Permaloff, 1986).

Some expert systems software are rule-based and amount to little more than a way of computerizing a decision tree

prepared beforehand by the social scientist. Such software does allow untrained users to be prompted for information using queries in ordinary English, after which the corresponding decision or choice is presented according to the rules embedded in the underlying decision tree.

Expert system generators, in constrast, allow the social scientist to construct a knowledge base, consisting of a data matrix of examples (values of independent variables and the dependent variable, measured at any level from nominal through ratio). The expert system generator software will use the knowledge base to construct automatically a set of rules which explain all cases of the dependent variable. The social scientist can refine this rule set in a variety of ways, such as eliminating outlier cases; eliminating rules which explain too few cases; by setting non-arbitrary cutting points; or by adjusting rules directly through an overriding if-then logic. The final rule set can be embedded in a computerized expert advisor system in which untrained users are asked multiple choice questions, following which a recommendation or prediction is made. It is also possible to chain expert systems together to construct very complex modularized decision systems.

B. Classification Algorithms in Expert System Generation

The computer software used later in this essay to illustrate social science application of expert systems is based on classification and rule development procedures called ID3 and developed by J. Ross Quinlan (1983) on the

basis of work by Hunt and Stone (1966) on the "Concept Learning System". Quinlan developed his algorithms from a series of experiments dealing with the discovery of efficient classification procedures from large numbers of examples, using the chess end game of king-rook versus king-knight as an illustration.

The ID3 classification algorithm produces by induction a decision tree which correctly classifies all given objects in an attribute domain. Compared to functional equivalents ID3 is particularly efficient, expecially in handling large numbers of objects.

The ID3 algorithm is simple. One starts with a rectangular data matrix of categorical data, with the values in one column defining the dependent classes to be predicted by the rule set to be generated. One independent attribute is selected and is used to partition the cases. If any partition is composed solely of members of a single class, then this partition becomes an end node in the decision tree. Otherwise additional attributes are selected to partition the knowledge base further into sub-partitions, sub-sub-partitions, and so on. Eventually all end node partitions will define only one class provided there are no objects of different classes having identical independent attribute values.

The challenge, of course, comes in selecting the partitioning attributes (and the cutting points which define attribute value categories for interval and rank data) such that the number of leaves (end nodes, each indicating a

rule) is minimized. It is in this area that Quinlan's work differed from that of Hunt.

ID3 uses an approach from information theory which minimizes the expected number of tests to classify an object by a given attribute (on computation, see Quinlan, 1983: 467-479). Each potential partitioning attribute is tested in turn to determine which can be expected to yield the most additional information on the dependent variable. Expected values are based on a logarithmic function of the proportion of cases in each leaf of the partition being examined in comparison with the proportion of cases in each class of the dependent variable.

The ID3 method will use the fewest independent variables necessary to reach a complete explanation of the dependent variable. Thus, frequently some independent variables in the knowledge base are ignored. (Identification and discussion of these redundant or irrelevant factors is itself a useful classroom exercise.)

For interval data, the ID3 method treats the mean of each pair of adjacent ordered values as a potential threshold (cutting point), then uses the method described above to select the threshold which can be expected to contribute the most information on the dependent variable. For purposes of setting thresholds, rank data are treated as interval. It is also possible in the case of rank and interval data, that the same independent variable will be used at two levels of the decision tree (e.g., for the

variable number of days, one level might use the cutting point more/less than 190 days, while a later level might use the cutting point more/less than 22 days).

C. A Computer Software Example: 1st-Class (Version 3)

The software used for demonstration purposes in this essay is 1st-Class, Version 3, from Programs in Motion, Inc., 10 Sycamore Road, Wayland, MA 01778; (617) 653-5093; $250. (A 10% educational discount is available, as are site licenses. Also, a limited scope version allowing five factors, six values, and ten examples is available for $50). It runs on the IBM PC/XT/AT series.

This software was chosen because of a number of features which may be worth noting. The program can import data matrices from Lotus 1-2-3, the leading microcomputer spreadsheet, and from a variety of other formats. Thus data used in analysis may be downloaded from a mainframe or edited with one's word processor.

The program can handle up to 32 variables with up to 32 categorical values, which is actually more than needed in most arenas since use of the maximum number of variables and values usually would result in excessively complex rule sets.

The 1st-Class software can induce a rule set from up to 240 examples, which was deemed a reasonable number of cases for a pilot or pretest study in exploratory phases of research. This case set size also seemed appropriate for split-halves reliability studies of the expert system, for

which the effective example size is thus 480. Moreover, larger data sets may be simulated by weighting of examples.

In addition to automatic application of built-in algorithms for inducing an expert rule set from a data matrix, 1st-Class allows three alternatives: (1) the automatic optimization algorithm may be overridden by user specification of the order of criterion variables; (2) the algorithm may be overridden by direct user editing of the rule screen (this feature allows 1st-Class to be used in a manner similar to rule-based expert systems); or (3) for numeric variables, the user may set his/her own cutting points rather than those selected automatically.

Several aspects of 1st-Class assist in data analysis. The rules in the expert system generated automatically are each associated with particular cases in the knowledge base. The cases that go with a given rule can be marked easily so that the researcher may better understand the case basis of each rule. Also, cases may be marked for temporary inactivation, allowing the social scientist to optimize a new rule set for the knowledge base without the marked cases. In addition, various statistical measures are automatically calculated for each rule (e.g., answer probability).

It should also be noted that 1st Class is supplied with a number of sample knowledge databases, including expert systems for diagnosing IBM PC hardware problems, for selecting among hazardous waste dump sites, for locating

appropriate references in a literature database, for selecting optimal educational media, for selecting suitable wines, and many others. The example perhaps closest to social science is based on an analysis of an historical database of tax court cases by Prof. Ronald M. Copeland. It illustrates how a few leading rules in the system can account for most of the examples in a knowledge base.

III. An Example: Explaining Variance in Legislative Satisfaction

The example selected is a reanalysis of data presented by Wayne L. Francis on factors thought to determine the variance in the extent to which state legislators are satisfied with legislative outcomes (Francis, 1985). These variables included:

chamber (House, Senate)
number of workdays
number of chamber bills
number of chamber bills passed
percent of chamber bills passed
number of bills from other chamber
number of bills from other chamber passed
percent of bills from other chamber passed
total bills received
total bills passed
percent passed of total bills
mean majority member satisfaction rating of outcomes by house and by decision to pass/not pass

The last variable listed was the dependent variable. Data were

collected for 1981 for 50 states, 99 chambers, yielding 198 satisfaction rating cases (Nebraska is unicameral; all other states had four satisfaction ratings: House pass, House not pass, Senate pass, Senate not pass).

On the basis of traditional regression analysis of these data, Francis concluded (p. 640): "we find that legislator satisfaction is dependent upon both the number of workdays and the bill passage rate." Francis infers that the former represent costs and the latter benefits of legislative service and concludes that legislators are rational actors in a political economy guided by cost-benefit logic.

Specifically, Francis finds the following relationships:

(1) majority party satisfaction ratings correlate -.43 with number of work days (19% of variance explained).

(2) majority party satisfaction ratios correlate in the .32 to .35 range (10 to 12% of variance explained), depending on chamber, with percentage of total bills passed by the chamber

(3) For decisions to defeat bills, the number of 1981 workdays and proportion of total bills passed together explain 23% of the variance in majority party mean satisfaction. This improved to 24% when an outlier, the N.H. Senate, was omitted.

(4) For decisions to pass bills, the corresponding percentage is 23%. This improved to 29% when the N.H. Senate was omitted. There is also a significant multiplicative effect of number of workdays and total passage rate for decisions to pass bills, although not for decisions to defeat.

A reanalysis of this dataset was undertaken to illustrate

the differing nature of the insights provided by inductive expert systems as compared to regression-based studies. It should be emphasized that the intent is not to show one approach "correct" or even necessarily better.

Subjecting the 198 cases of the Francis study to the ID3 algorithm resulted in a 51-rule system explaining all 198 cases (see Appendix A). In this system, nine rules explained 50% of the cases (99) while many rules were particular to only one or two cases. This sort of over-complex model sacrifices parsimony of explanation in favor of 100% explanation of cases and is common in analysis of social science topics. The resulting complex and detailed expert system reflects numerous arbitrary rules created to "explain" particular examples.

One way to refine such expert systems is to undertake an iterative process in which examples are deleted from the knowledge base in each case where the rule explains only one or two cases. Deletion leads to the setting of alternate threshold values and, often, improvement in the model. In this study, seven iterations were undertaken until a model was arrived at in which each rule explained at least three examples:

Iteration	# Cases	# Rules	Parsimony
1	198	51	9 rules explain 99 cases
2	162	36	8 rules explain 99 cases
3	140	18	7 rules explain 99 cases
4	137	18	8 rules explain 105 cases
5	131	17	7 rules explain 102 cases
6	126	13	6 rules explain 102 cases
7	122	10	6 rules explain 103 cases

The final model is listed in Appendix B. Its six leading rules explain 52% of the 198 cases in the original knowledge base. (This is not the same as explaining 52% of the variance, as might be cited in regression analysis. The six leading rules fully identify 103 or 52% of cases, not counting at all many other cases which "come close"). These six rules explain low (<2.5), medium (2.5 - 2.99), and high (>=3.0) levels of mean majority party legislative satisfaction:

(1) Low satisfaction results if the number of days is less than 93.5 and the percent of chamber bills passed is more than 68%. N = 16.

(2) Low satisfaction also results if the number of days is less than 93.5 and the percentage of chamber bills passed is less than 68% but the number of bills from the other chamber is more than 328.5, the number of total bills passed is less than 677.5, and the total number of chamber bills is more than 757. N = 18.

(3) High satisfaction occurs when there are more than 93.5 days, more than 860.5 chamber bills, and fewer than 46% of them passed. N = 11.

(4) Medium satisfaction occurs when there are fewer than 93.5 days, less than 68% of chamber bills passed, fewer than 328.5 bills from the other chamber, and more than 134 of them passed. N = 31.

(5) Medium satisfaction also occurs when there are fewer than 93.5 days, less than 68% of chamber bills passed, more than 328.5 bills from the other chamber, and more than 677.5 of them passed. N = 9.

(6) Medium satisfaction also occurs when there are more than 93.5 days but less than 860.5 chamber bills. N = 18.

A quick but misleading interpretation of these data is to note that regression analysis explained under 30% of the variance in the dependent variable, whereas inductive expert systems fully explains over 50% of the given cases. A better intepretation is to observe that expert systems tend to explain more, but they do so in a richer and more complex way. That complexity is less easy to summarize, however. Neither methodology is intrinsically better. At the hypothesis-formation stage of research, though, the added richness of the expert systems approach may be quite valuable to the social scientist.

For example, correlation analysis shows a moderate negative relation (-.43) between satisfaction and work days. When session length is combined with passage rate, the multiple regression coefficients for session length are also negative with length being a more important determinant than passage rate. From this one infers that the more days legislators are in session, the less they are satisfied. One also concludes that there is a weaker but significant relationship such that the more total bills passed, the higher the satisfaction.

What does expert systems lead one to conclude? If the session is long and there are many chamber bills, but the legislature is rejecting most of them, majority party mean satisfaction will be high (Rule 3). Conversely, if the session is short and the bulk of chamber bills are being passed,

satisfaction will be low (Rule 1). Moreover, if the session is short and many chamber bills are being defeated, there will still be low satisfaction if there are many bills from the other chamber, and relatively few total bills passed though the total bills from both chambers is high (Rule 2). There are several intermediate possibilities which lead to medium satisfaction (Rules 4 - 6).

Put another way, expert systems results suggest that it is satisfying to have a long time to consider bills and reject many of them. It is dissatisfying to have a short time to consider bills and wind up accepting most. If time is short, even if one is rejecting many, it is still dissatisfying if one is being inundated with bills from the other chamber and has a high total to consider overall.

Where regression analysis led to a conclusion whose hypotheses are drawn from political economy (pass the most bills [benefits] per time period spent [costs]), inductive expert systems leads to an information process model. In the former, satisfaction has to do with rational economic consideration of costs and benefits. In the latter, satisfaction has to do with the the role of the decision-maker in relation to the level of information input requiring decision.

This essay is not arguing that the information process model generated by the inductive expert systems methodology is "correct" and the political economic model generated by multiple regression analysis is "incorrect". Rather, a simple point is being made: the inductive expert systems methodology can be a significant supplement to regression-based techniques now

dominant in social science. Their use could enhance the richness of the research process, particularly in the exploratory hypothesis formation stage. Given the advent of inexpensive microcomputer-based software for expert systems generation, there is every reason to integrate expert systems methodology into social science research methods courses and to rehabilitate thereby the traditional importance of induction from example.

IV. The Role of Inductive Expert Systems in the Social Science Research Process: A Conclusion

Expert systems generators such as 1st Class should be thought of as generators of exploratory hypotheses. They make trivial the task of inducing an exploratory rule set from a database. The rules are, in fact, hypotheses consistent with one's data. They can be validated by replication using other data sets. For example, in a study on jury selection, rule sets may be developed for selecting jurors favorable toward conviction in certain classes of cases, working inductively from data developed in one year or jurisdction and validated for other years or jurisdictions, or through the split halves method.

For instructional purposes, faculty could use packages of the sort reported here to generate analysis and discussion. In a course on conflict, for example, students might be given data for which the dependent variable were factors associated with the occurrence of labor strikes. Each student could be asked to indicate whether he/she though the values for each case would be associated with a strike or not. Each student's completed data matrix could be used to generate an expert rule set. The

instructor could sort these rule sets into two or more common types. Class discussion could focus on comparison of alternative student rule sets, and each with the rule set induced from actual data on labor strikes.

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APPENDIX A

Initial Rule Set, Iteration 1

(Lines = 101; rules = 51; cases = 198; 9 rules explain 99 cases)

```
    ---- start of rule ----
 1: #1981 days??                                          Satisfaction
 2:     <96.00:#ch passed??                                  Level
 3:       <0.68:chamber??
 4:        House:#1981 days??
 5:           <44.00:#ch passed??
 6:             <0.31:#1981 days??
 7:               <37.50:----------------------------2.5 2.99
 8:               >37.50:Decisions??
 9:                Pass:-----------------------------<2.5
10:                Not pass:-------------------------2.5 2.99
11:             >0.31:----------------------------------<2.5
12:           >44.00:Decisions??
13:            Pass:total recd??
14:               <1792.50:#ch bills??
15:                 <470.00:#1981 days??
16:                   <50.00:---------------------2.5 2.99
17:                   >50.00:---------------------<2.5
18:                 >470.00:----------------------2.5 2.99
19:               >1792.50:#ch bills??
20:                 <1930.50:---------------------<2.5
21:                 >1930.50:#ch bills??
22:                   <2571.00:---------------------2.5 2.99
23:                   >2571.00:---------------------<2.5
24:            Not pass:total recd??
25:               <593.00:----------------------------3.0 3.49
26:               >593.00:#ch bills??
27:                 <1126.00:#1981 days??
28:                   <88.00:---------------------2.5 2.99
29:                   >88.00:---------------------<2.5
30:                 >1126.00:total recd??
31:                   <1812.00:#other bill??
32:                     <243.50:--------------------2.5 2.99
33:                     >243.50:--------------------3.0 3.49
34:                   >1812.00:#1981 days??
35:                     <76.00:---------------------2.5 2.99
36:                     >76.00:#ch passed??
37:                       <666.50:--------------------2.5 2.99
38:                       >666.50:--------------------3.0 3.49
39:        Senate:#ch passed??
40:           <0.55:total recd??
41:             <1985.50:#other bill??
42:               <498.00:#1981 days??
43:                 <67.00:#1981 days??
44:                   <37.50:---------------------<2.5
45:                   >37.50:Decisions??
46:                    Pass:#ch passed??
47:                       <0.27:--------------------<2.5
48:                       >0.27:#ch passed??
```

```
                                <0.53:----------2.5 2.99
                                >0.53:----------<2.5
                          Not pass:----------2.5 2.99
                        >67.00:#1981 days??
                          <90.50:----------<2.5
                          >90.50:Decisions??
                           Pass:----------<2.5
                           Not pass:----------2.5 2.99
                      >498.00:----------<2.5
                     >1985.50:#1981 days??
                       <59.00:Decisions??
                        Pass:----------2.5 2.99
                        Not pass:----------3.0 3.49
                       >59.00:#1981 days??
                         <66.00:Decisions??
                          Pass:----------<2.5
                          Not pass:----------2.5 2.99
                         >66.00:----------2.5 2.99
                  >0.55:----------2.5 2.99
              >0.68:#oth passed??
                <413.00:----------<2.5
                >413.00:Decisions??
                 Pass:#1981 days??
                    <45.00:----------<2.5
                    >45.00:----------3.0 3.49
                 Not pass:----------2.5 2.99
            >96.00:%ch passed??
              <0.22:----------3.0 3.49
              >0.22:total% pass??
                <0.59:%oth passed??
                  <0.63:#1981 days??
                    <112.00:Decisions??
                     Pass:#1981 days??
                        <106.50:----------3.0 3.49
                        >106.50:----------<2.5
                     Not pass:----------2.5 2.99
                    >112.00:----------2.5 2.99
                  >0.63:#1981 days??
                    <111.50:----------2.5 2.99
                    >111.50:----------3.0 3.49
                >0.59:#ch passed??
                  <454.00:#ch bills??
                    <478.00:Decisions??
                     Pass:----------<2.5
                     Not pass:----------2.5 2.99
                    >478.00:----------2.5 2.99
                  >454.00:Decisions??
                   Pass:#ch bills??
                      <1843.50:----------<2.5
                      >1843.50:----------2.5 2.99
                   Not pass:#ch bills??
                      <1843.50:----------2.5 2.99
                      >1843.50:----------<2.5
---- end of rule ----
```

APPENDIX B

Final Rule Set, Iteration 7

(Lines = 19; rules = 10; cases = 122; 6 rules explain 103 cases)

```
    ---- start of rule ----
 1: #1981 days??                                          Satisfaction
 2:   <93.50:%ch passed??                                     Level
 3:            <0.68:#other bill??
 4:                    <328.50:#oth passed??
 5:                              <134.00:%ch passed??
 6:                                        <0.28:-----2.5( 2.99
 7:                                        >0.28:-----<2.5
 8:                              >134.00:-------------2.5( 2.99
 9:                    >328.50:#ch passed??
10:                              <677.50:#ch bills??
11:                                        <757.00:----2.5 2.99
12:                                        >757.00:----<2.5
13:                             >677.50:-------------2.5 2.99
14:            >0.68:-----------------------------------<2.5
15:   >93.50:#ch bills??
16:            <860.50:--------------------------------2.5 2.99
17:            >860.50:%ch passed??
18:                      <0.46:-----------------------3.0 3.49
19:                      >0.46:-----------------------2.5( 2.99
    ---- end of rule ----
```